MACHINE-LEARNING DRIVEN CORRELATION STUDIES: MULTI-BAND FREQUENCY CHIRPING AT NSTX

B. J. Q. WOODS, V. N. DUARTE, E. D. FREDRICKSON, N. N. GORELENKOV, M. PODESTÀ

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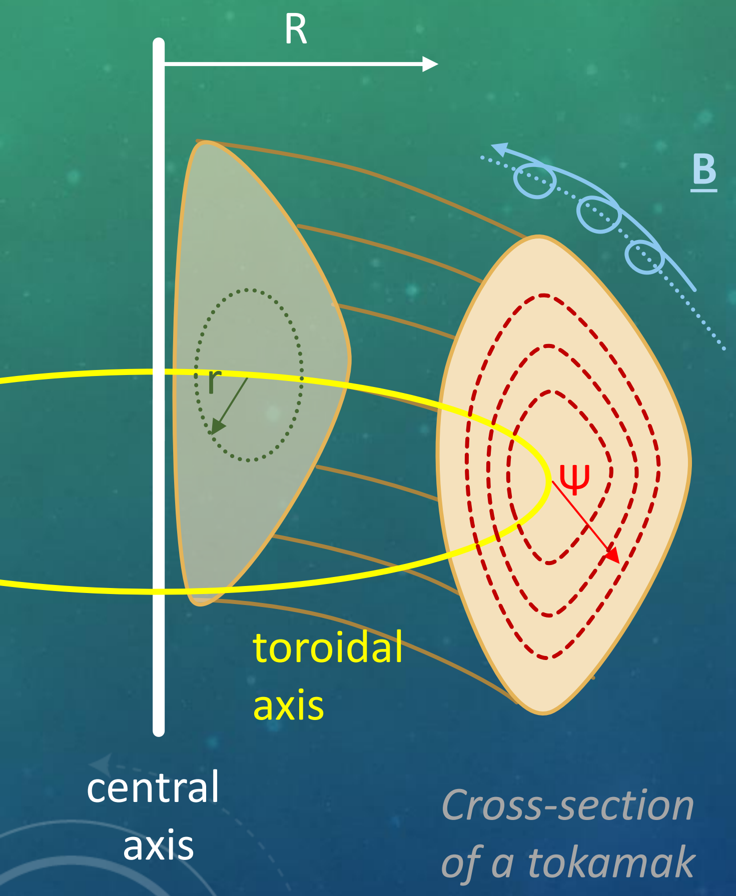
e: benjamin.woods@york.ac.uk

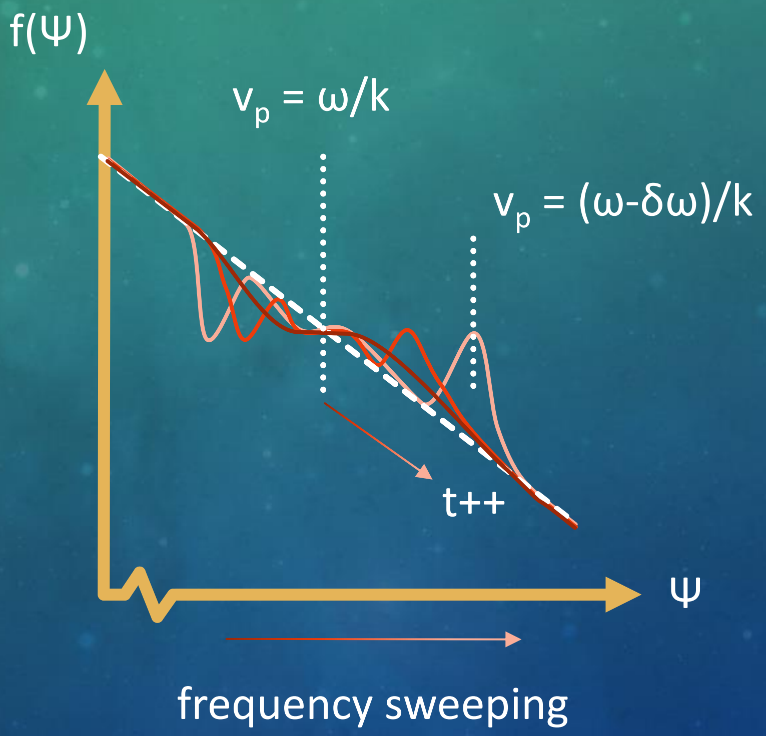
SEMINAR CONTENT

- **Brief introduction to mode avalanching**
- **Machine learning for chirping characterisation**
- **Mode character correlations on NSTX**

BRIEF INTRODUCTION TO MODE AVALANCHING

FAST ION LOSS VIA RESONANT INSTABILITIES





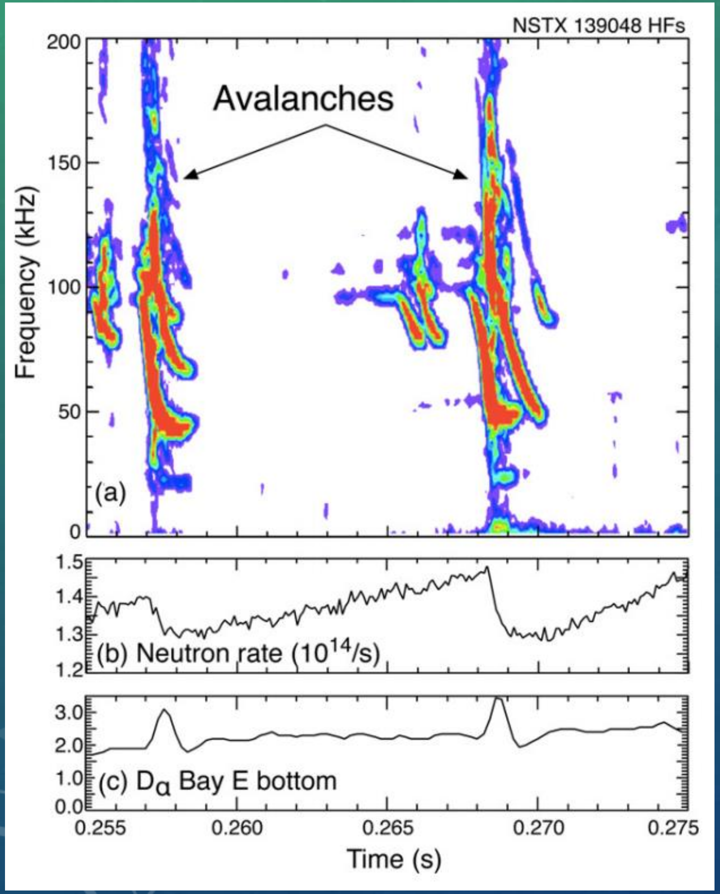
Resonant instability

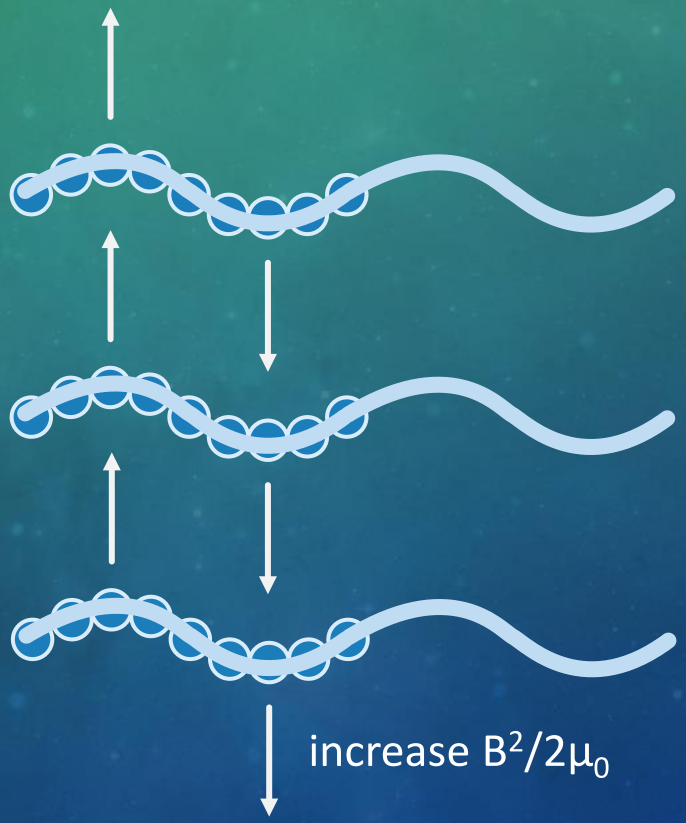
- Fast ion distribution is peaked near the toroidal axis
- Some particles resonate with the EM field (c.f. inverse Landau damping)
- **Frequency sweeping**
- **Fast ion transport mechanism**

$$\boxed{p_\varphi = mRv_\varphi - q\Psi}$$

ALFVÉNIC AVALANCHING

Magnetic fluctuations from NSTX [1]





Alfvén waves

- MHD wave
- **Subject to kinetic instability**
- Compressional branch is analogous to acoustic wave

Fast ion loss correlated with drop in neutron rate during "avalanches"

Research questions:
?: What causes mode avalanching?
?: How can we stop it?

[1] E.D. Fredrickson *et al.* 2013 NF **53** 013006

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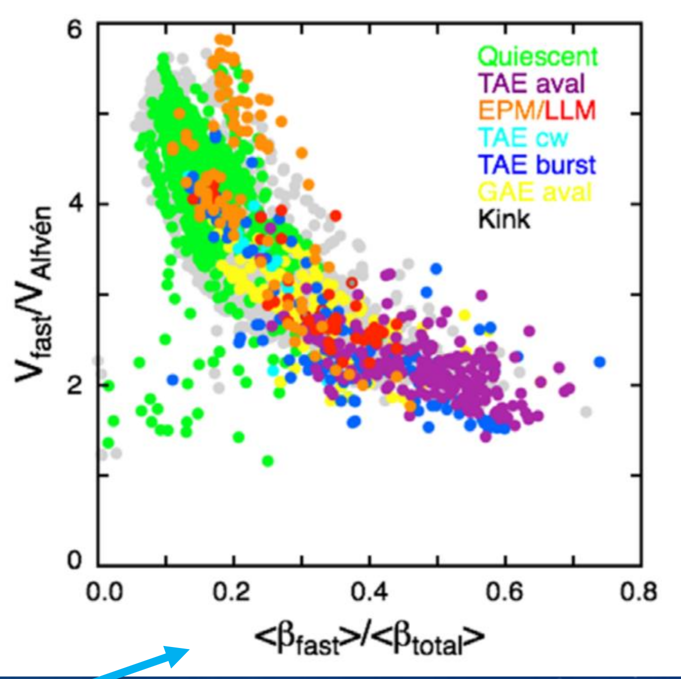
MACHINE LEARNING FOR MODE CHARACTERISATION

MACHINE LEARNING FOR FUSION APPLICATIONS

- Vast increase in speed for certain tasks
  - Data analysis can be done faster
  - Computational predictions can be extracted faster
  - May prove **vital** for operational performance of a tokamak
- Can we train an AI to recognise and characterise chirping?
  - Potentially feed into overall control system
- Knowledge of correlations between plasma parameters and mode character is **key**
  - i.e. turbulent suppression of mode chirping [3,4]

[2]

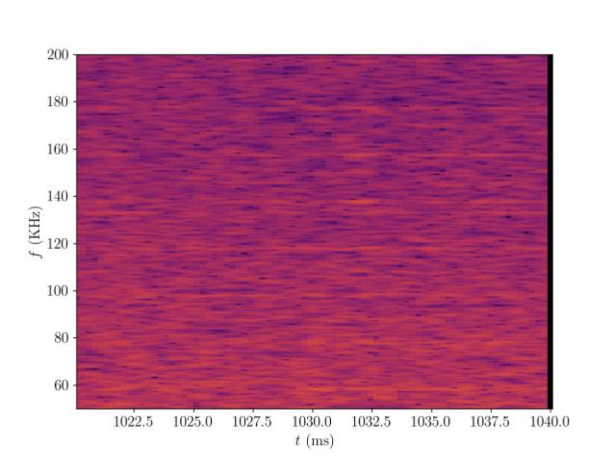


very time consuming to produce

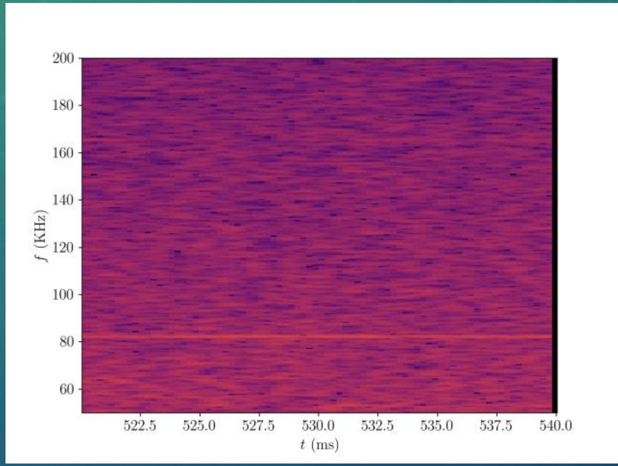
only 2 parameters

[2] E. D. Fredrickson *et al.* 2014 NF **54**, 093007
[3] V. N. Duarte *et al.* 2017 NF **57**, 054001
[4] B. J. Q. Woods *et al.* 2018 NF **58**, 082015

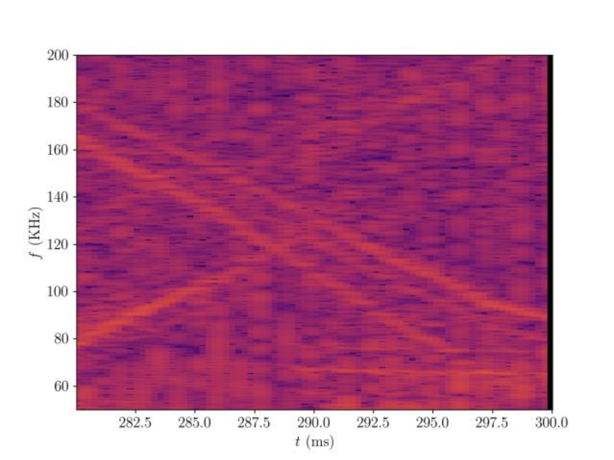
MODE CHARACTER CATEGORIES



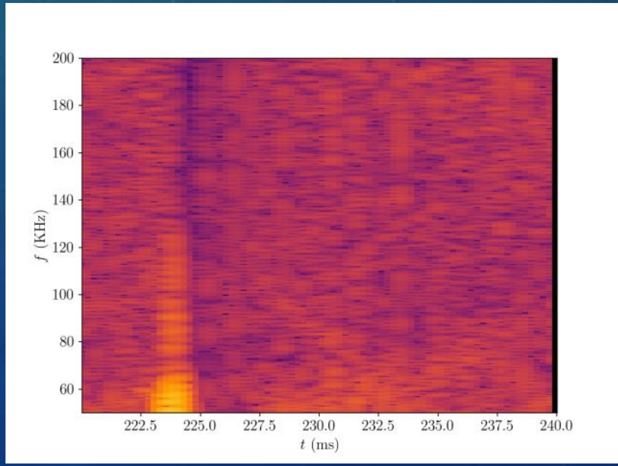
Noise/quiescence



Fixed frequency



Chirping



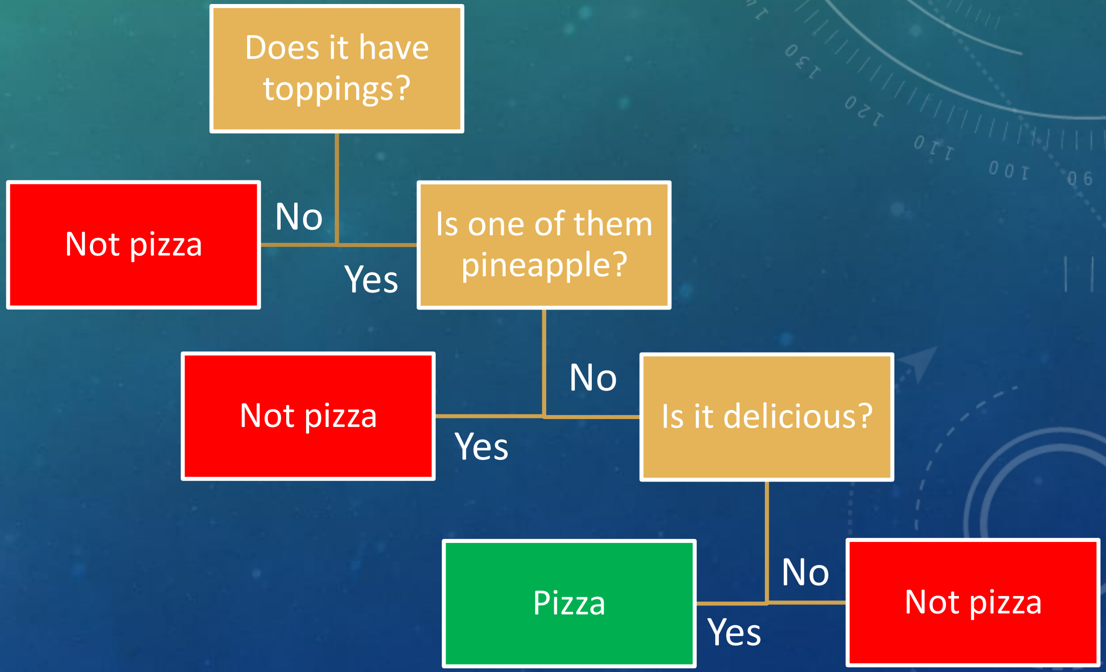
Avalanching

(Shots 127109, 134851)

DECISION TREE CLASSIFICATION

- Human classification can be broadly considered as a flowchart, or decision tree
- The maximum depth of the tree is the maximum number of decisions

Pizza classification



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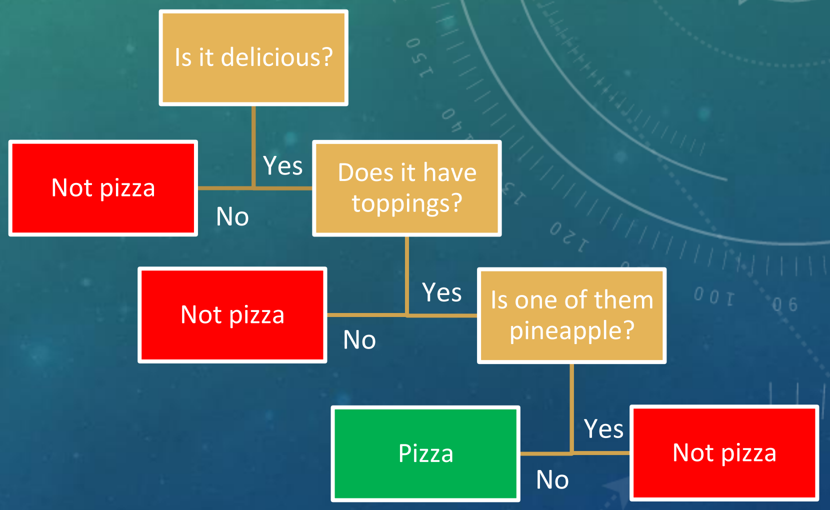
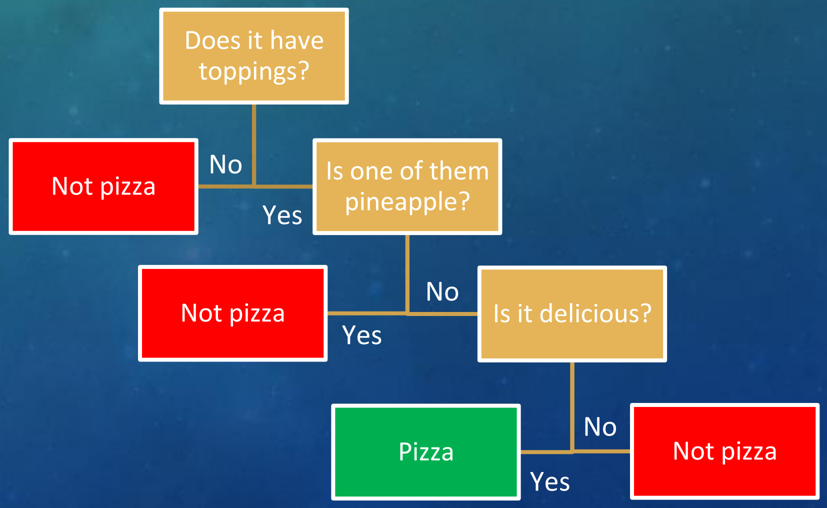
DECISION TREE CLASSIFICATION

- In principle, there is a **free choice of decision tree**
  - We can ask different questions
  - We can permutate questions
- Each tree **should lead** to the same overall outcomes

Pizza classification 2



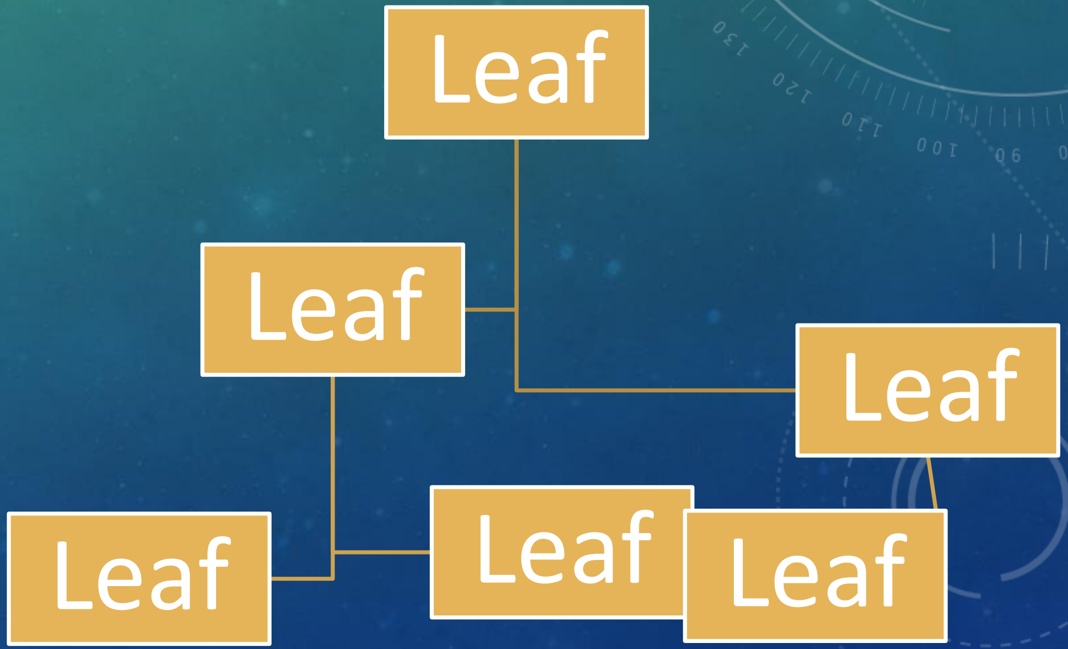
Pizza classification 1



DECISION TREE CLASSIFICATION

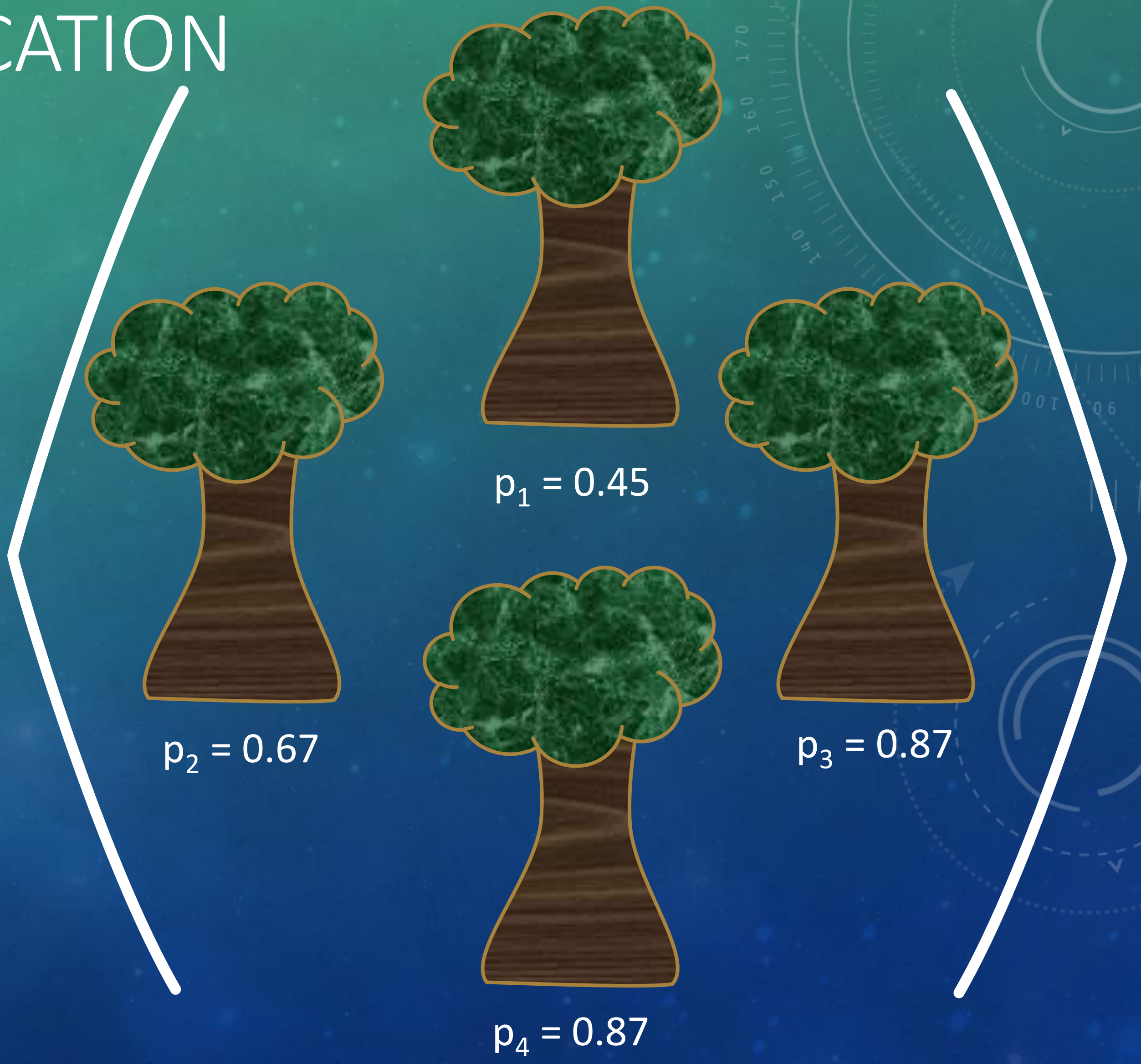
- A simple AI decision tree creates a “decision” (leaf), and places weights against the data
- After optimizing the weights by testing against the training set, it splits and creates more leaves based on probability of success
- Each branch (path between leaves) has a maximum depth
  - After training, the path taken through the tree depends on the found weights
- **Highly random structure**
  - Probability of successful classification varies from tree to tree
- Make the tree too deep - **overfit**
- Make the tree too shallow - **underfit**

Pizza classification (AI)



RANDOM FOREST CLASSIFICATION

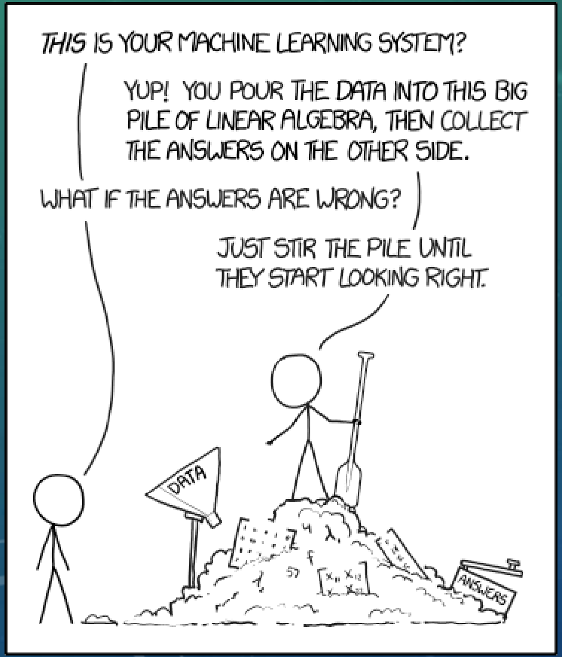
- Take an **ensemble** of trees, and take an average classification
- Linear average (mean) yields the mean accuracy
- Non-linear averages (mode, RMS) can yield higher accuracy than the mean
  - If the standard deviation in accuracies is low



OVERALL TRAINING FRAMEWORK

Training shot list → Grab NSTX data (BASH, IDL) → Pick frequency band (i.e. 1-30 kHz) → Produce STFT processed data (Python) → Plot data and perform human characterization (Python) → Tweak AI parameters → Train AI (Python)

tweak parameters



[5]

The AI operates as a multi-class classifier:

- 4 **separate** classifiers (quiescent, fixed-freq, chirping, avalanching)
- Each classifier is a random forest in **scikit-learn**
  - Maximise probability by changing **no. of trees** and **branch depth (pruning)**
- Characterisation sits in a hierarchy (aval. > chirp. > fixed-freq. > quie.)

Take highest prob.

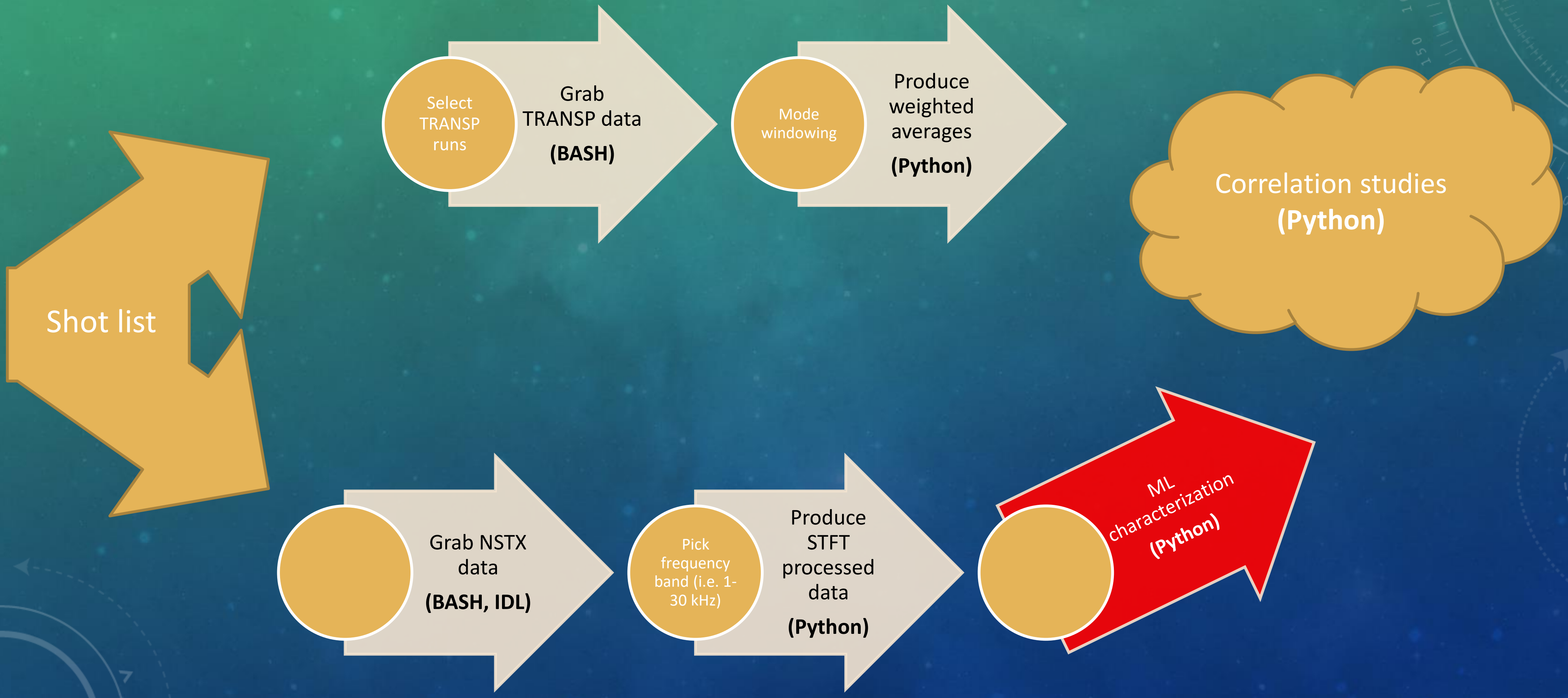
$$p \leq \max(p_i)$$

Take hierarchal prob.

$$p \leq \prod_{i=1}^{4} p_i$$

[5] http://xkcd.com/1838

OVERALL CORRELATION FRAMEWORK



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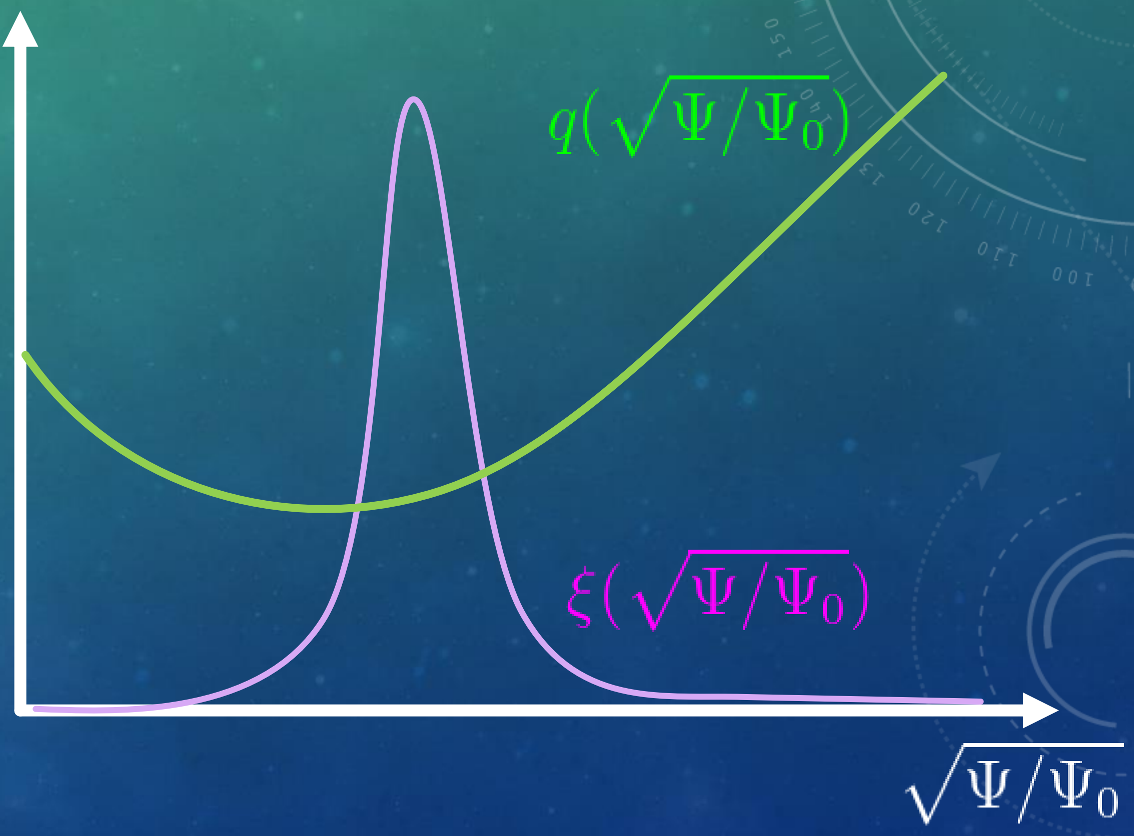
WEIGHTED AVERAGES

- Chirping is a non-linear phenomenon
- Requires wave-wave or wave-particle nonlinearity
- **Aim:** correlate chirping with plasma parameters
  - These parameters can be spatially dependent
- **Solution:** take weighted averages
  - Weighting is a normalised ‘window function’ which mimics mode structure

$$\langle g \rangle \equiv \int_0^1 (g \cdot w)\, \mathrm{d}\sqrt{\Psi/\Psi_0}$$



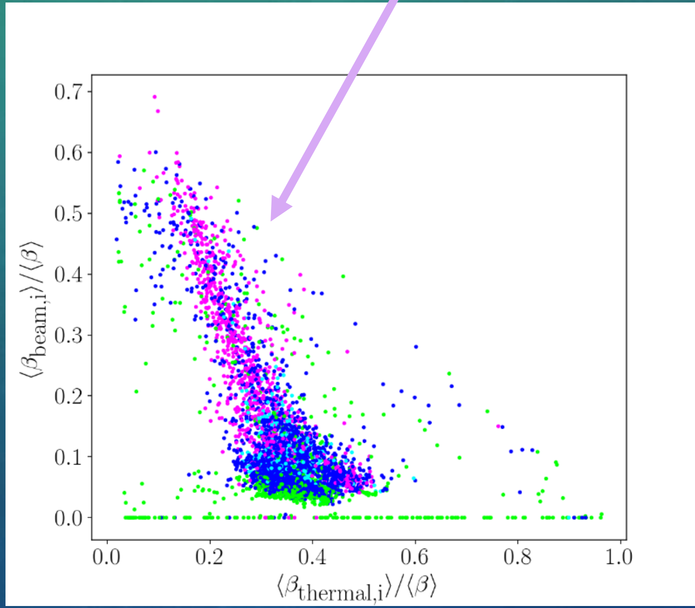
BEAM ION BETA

Measure of fast ion resonant drive

- Low freq. modes:
  - Avalanche at high %
- TAEs:
  - Significantly less avalanching

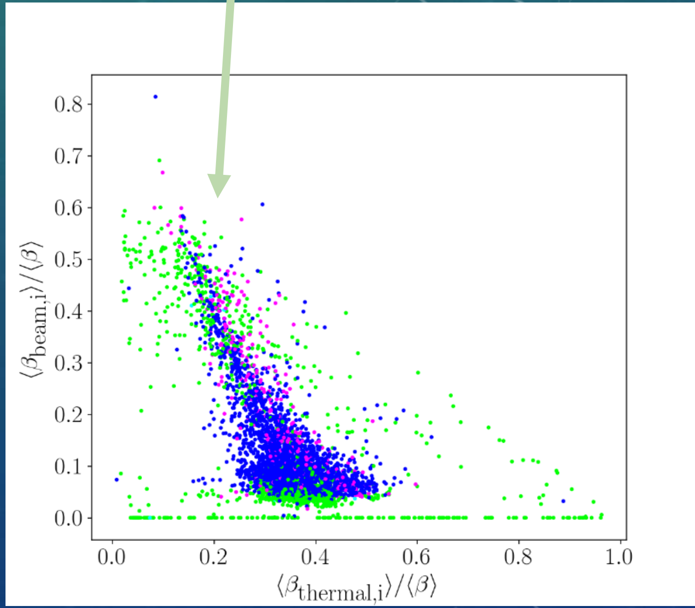
Generally at high beam ion beta, fishbones are very active while TAEs are less active

more avalanching



kink/tearing/fishbones
(1-30 kHz)

more quiescence



TAEs
(50-200 kHz)

quiescent – fixed freq. – chirping – avalanching

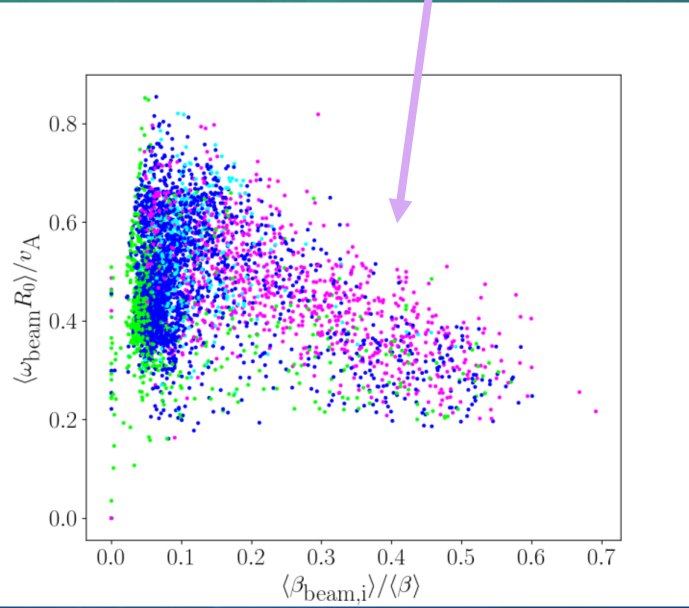
BEAM TOROIDAL VELOCITY

Measure of fast ion average velocity

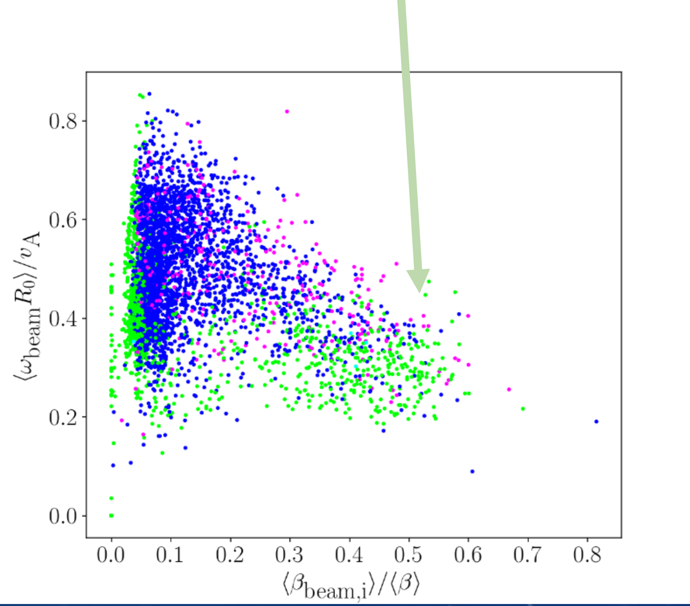
invariant w.r.t BTV

slight preference w.r.t BTV

- Low freq. modes:
  - BTV not key factor for chirping
- TAEs
  - More quiescent at similar values of BTV for high beam ion beta



kink/tearing/fishbones
(1-30 kHz)



TAEs
(50-200 kHz)

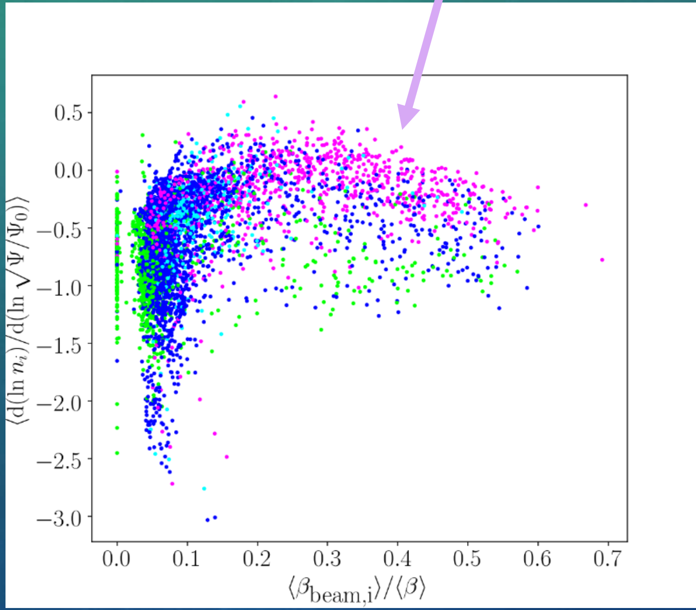
quiescent – fixed freq. – chirping – avalanching

NORMALISED ION DENSITY GRADIENT

Measure of MHD stability

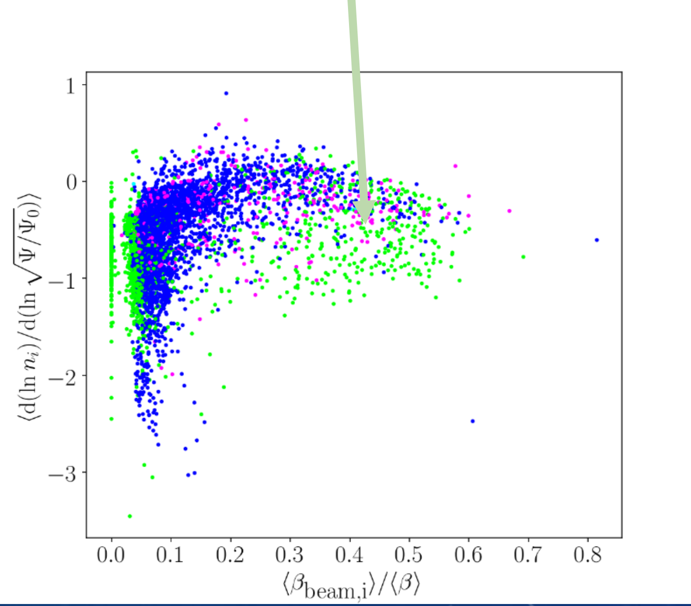
- Low freq. modes:
  - More avalanching/chirping at high beam beta
- TAEs:
  - More quiescence at high beam beta

more avalanching



kink/tearing/fishbones
(1-30 kHz)

more quiescence



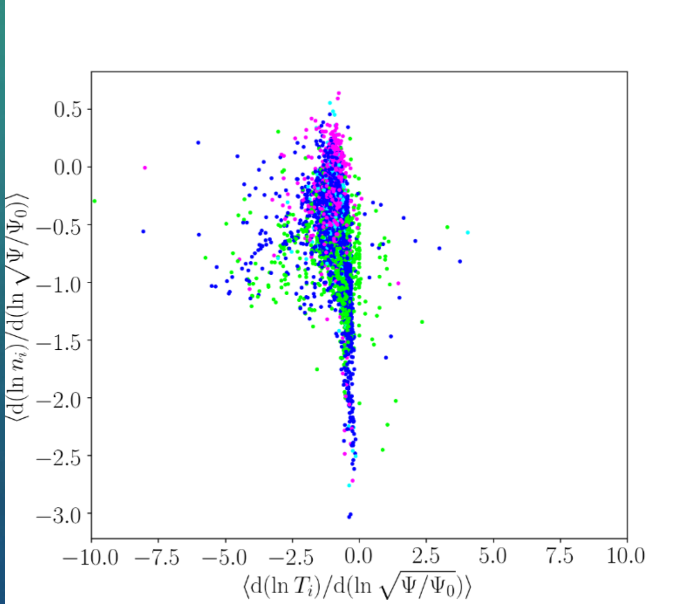
TAEs
(50-200 kHz)

quiescent – fixed freq. – chirping – avalanching

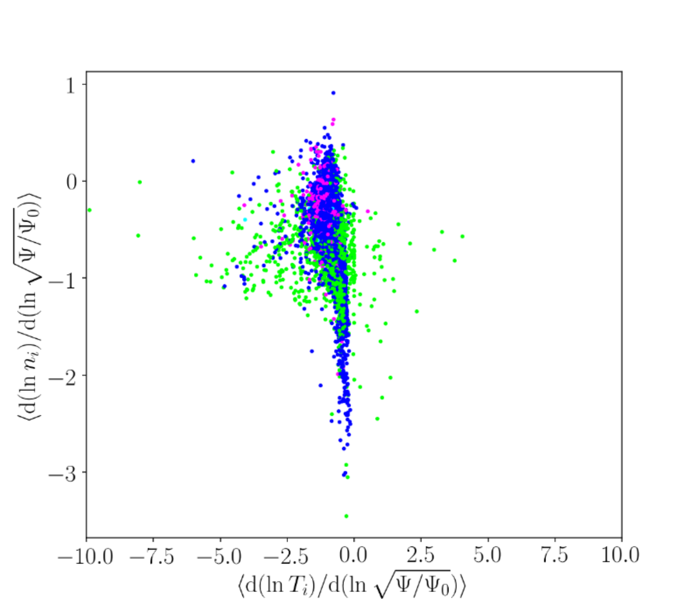
TEMPERATURE AND PRESSURE GRADIENTS

Measure of MHD stability

- Both feature a window of increased quiescence
  - Modes here intermittently chirp
- At high $|n_i'|$, decreased quiescence
  - Modes here continuously chirp
- At $n_i' > -0.5$, increased avalanching?
  - Profile inversion/flattening due to large scale chirping/avalanching? (see [6])



kink/tearing/fishbones
(1-30 kHz)



TAEs
(50-200 kHz)

quiescent – fixed freq. – chirping – avalanching

[6] Y. Todo *et al.* 2014 NF **54**, 104012

SUMMARY

- Particle resonance can lead to fast ion loss
- Machine learning offers a promising future for rapid characterisation of active modes in a tokamak
- Preliminary results show interesting correlations
  - Mode character depends strongly on beam beta
  - $|n_i'|$ may indicate hysteresis

Thanks for listening!

[1] E.D. Fredrickson *et al.* 2013 NF **53** 013006
[2] E. D. Fredrickson *et al.* 2014 NF **54**, 093007
[3] V. N. Duarte *et al.* 2017 NF **57**, 054001
[4] B. J. Q. Woods *et al.* 2018 NF **58**, 082015
[5] http://xkcd.com/1838
[6] Y. Todo *et al.* 2014 NF **54**, 104012